Knowing Me, Knowing You

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Knowing Me, Knowing You: Datafication on Music Streaming Platforms

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Abstract
This chapter explores how data is collected and used to personalise the listening experience on contemporary streaming platforms. Focusing on Spotify's 'Discover Weekly' feature and on the growing importance of context-aware recommendation systems, the chapter concludes by looking at some of the wider implications of 'datafication' for the future of music consumption and discovery.

Keywords**:** datafication; streaming; Spotify; recommendation; context.

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Since the invention of the phonograph in 1877, the individual act of listening to recorded music has been largely shrouded in mist, hidden from the prying eyes of marketers and the music industry. What people listened to, how often they listened to it, when and where it was listened to, were always at best a guess.[1] Even after Nielsen began employing the SoundScan media measurement system in 1992, the music–data feedback loop did not extend much beyond the record store checkout counter. What became of an album was unknown once it left the record shop. Perhaps it became the soundtrack for a teenage summer. Or maybe it was purchased as an ill-advised gift, never to be listened to again. The fog that blanketed the music radio audience was almost as impenetrable. Diary or survey-based measurement systems rely on the often faulty memories and perceptions of listeners. Automated wearable devices such as Nielsen's Portable

[1] Certain aggregate listening experiences have generated real-time data in the past. For example, in the heyday of the jukebox, the music tastes of precise locales could be determined thanks to mechanised play meters that were built into the boxes (Harvey, 2014).

People Meter attempted to solve these problems, but in the process generated new controversies about their reliability (Boudway, 2016). “[R]adio ratings,” Passoth et al (2014, p. 279) conclude, “have always been artificial and problematic.”

As music listening has moved online, the gap between what Philip Napoli (2003) terms the *measured* listening audience and the *actual* listening audience has appeared to shrink, if not disappear entirely. Online listening generates a data trail that provides detailed insight into individual listeners and listening practices (Baym, 2013). This “datafication of listening” (Prey, 2016) has accelerated with the mainstreaming of music streaming platforms. However, data never merely reflects reality; it always constructs that which it measures at the same time. This chapter will explore the ‘what’ and ‘how’ of datafication on music streaming platforms, and some potential implications.

Music Streaming and Recommendation

According to the Recording Industry Association of America, revenues from streaming overtook revenue from CDs or digital downloads for the first time in 2015 (Friedlander, 2016). Taken together, on-demand music streaming services such as Spotify, Apple Music and Deezer, and personalised online radio services like Pandora Internet Radio, are the fastest-growing sector of the global music industry and represent the future of music distribution and consumption in a post-download era (IFPI 2015).

What truly distinguishes these services from previous forms of music consumption, however, is the data feedback loop they generate in real time. On contemporary music streaming services all listening time is data-generating time. Music streaming services are able to collect and store data on listeners in a vast array of different ways. Spotify, for example, first collects information upon registration for the service.[2] This information may include one's username, password, email address, date of birth, gender, address, postal/zip code, and country. If the user chooses to register for Spotify through a third party such as Facebook, Spotify gains access to the user's Facebook profile and information such as networks, names and profile pictures of contacts. Once a new user begins listening to music, Spotify records all interactions with content such as songs and playlists (favorites, skips, repeats, etc.) and interactions with any other services offered or linked to Spotify. For instance, if the user integrates their Spotify account with Facebook, Spotify gains access to their publicly available activity on that platform. Technical data is also collected through numerous methods, such as cookies, unique device IDs, and motion or orientation-generated mobile sensor data. A Spotify user may also give the service permission to access their personal photos and specific location through their mobile device's GPS or Bluetooth.

These are just some of the ways that Spotify is able to collect data on its listeners, as described in more detail in Spotify's most recent privacy policy (Spotify Privacy Policy, 2016). These methods of data collection and storage are much the same across all streaming services (Prey, 2015). Aside from facilitating the basic technical operations of these services, the harvesting and analysis of vast troves of listener data permits the mass customization and personalisation of the listening experience. As stated in Spotify's most recent privacy policy, Spotify requires such data:

> …to provide, *personalise*, and improve your experience with the Service and products, services, and advertising (including for third party products and services) made available on or outside the Service (including on other sites that you visit), for example by

[2] Information compiled in the following paragraph is taken from Spotify's most recent privacy policy for Canadian users; effective as of November 1, 2016 and available at https://www.spotify.com/ca-en/legal/privacy-policy/

> providing *customised, personalised, or localised* content, recommendations, features, and advertising on or outside of the Service” (ibid., emphasis added).

Clearly, the emphasis in the above explanation is on ‘personalisation’. Most of the leading streaming platforms have libraries of over 30 million tracks - more music than anyone could listen to in a lifetime. Unable to build a competitive advantage through the sheer size of their catalogues, these platforms are each attempting to perfect the art of personalisation and prediction: giving listeners exactly what they want, and what they don’t yet know they want. The assumption is that the more accurately a streaming service is able to zero in on the tastes of the individual listener, the more time the listener will spend on a service, and the higher the likelihood that they will convert to a paid subscription package.

Today, all the leading music streaming platforms have developed their own recommendation systems. In a highly competitive, and cut-throat market, whoever wins the recommendation battle could win the streaming music wars (IFPI, 2015). This represents a sea change in how the music industry operates. With listeners drowning in choice, “[w]hat used to be a question of persuasion”, writes Eric Harvey (2014), “has become a problem of prediction.”

In what follows I will provide a rough sketch of some of the ways that streaming services attempt to solve this ‘problem of prediction’. I will begin by describing one of Spotify’s most prominent recommendation systems: Discover Weekly. I will then move to a discussion of the growing importance of context-aware recommendation systems. This chapter will conclude with a brief discussion of some of the wider implications of datafication for the future of music discovery and consumption.

Spotify's 'Discover Weekly'

With over 140 million active users, Spotify is the global leader in music streaming. Subscribers to Spotify will likely be familiar with 'Discover Weekly', a personally tailored playlist of 30 new tracks that is delivered to each subscriber every Monday morning. Since it was introduced in July 2015, Discover Weekly has been one of Spotify's most successful products. Over 40 million listeners have turned to Discover Weekly for personalized playlists, streaming 5 billion tracks in the process (Spotify Press, 2016). To understand how Discover Weekly personalizes music, we need to first understand how Spotify 'maps' the vast world of online music, and from this, creates a 'taste profile' for each individual listener.

Spotify improved its music data analytics capabilities significantly when it purchased The Echo Nest, a Boston-based data analytics start-up, in 2014. The Echo Nest treats music taste correlation as a scientific problem that can be solved by huge data sets. The Echo Nest accomplishes this seemingly Sisyphean task by turning both music, and conversations about music, into quantifiable data. Utilizing acoustic analysis software to process and classify music according to multiple aural factors - from its pitch to its tempo to its danceability - their system "ingests and analyzes the mp3, working to understand every single event in the song, such as a note in a guitar solo or the way in which two notes are connected" (as cited in Darer, 2012). As The Echo Nest co-founder and CTO Brian Whitman explained: "[t]he average song has about 2000 of these 'events' for the system to analyze. It then makes connections between that song and other songs with similar progressions or structures" (ibid).

At the same time, The Echo Nest conducts semantic analysis of online conversations about music that take place every day, all over the world — millions of blog posts, music reviews, tweets and social media discussions. They do this by compiling keywords found in descriptions of the music and its creators and then linking them to other artists and songs that have been described with similar keywords and phrases (The Echo Nest, 2014). This data is used to determine song similarities on a more cultural level. For example, while a Christian rock band might sound similar to an indie rock band, fans of the two inhabit different discursive spheres.

Once the world of music has been mapped, the task then becomes to figure out where each individual listener fits on this map, and their individual movements through music space. To this end, The Echo Nest developed a preference analytics and visualization tool called the 'Taste Profile'. Taste Profiles are organized into music segments. Such segments are categorized in numerous ways: for example, artist- and genre-based segments (ie. listeners who like Beyonce but also like Punk music). Other segments are built from listener behavior (ie. listeners who prefer diversity and discovery). Every interaction a listener has with a musical item – including the listener's music tastes (selected artists and songs) and music behavior (favorites, ratings, skips, and bans) – is captured and recorded in real-time (ibid.). The Taste Profile is thus a dynamic record of one's musical identity and "the foundation of personalization at Spotify", according to Ajay Kalia, who oversees the project at the company (Heath, 2015).

Spotify's premier recommendation service 'Discover Weekly' is built atop your Taste Profile, but it is a hybrid recommender system; combining content-based filtering of the Taste Profile with its own take on collaborative filtering ("those who bought X also bought Y"). Discover Weekly first combs through Spotify's massive collection of playlists to find lists that include the songs and artists you love. Next, it identifies the songs on those playlists that you haven't heard. Finally, it filters those songs through your Taste Profile, in order to only select songs that match the particular type of music fan that you are.

Thus, while Spotify builds a unique music identity profile for each listener, Discover Weekly also relies heavily on other people’s tastes. In a press release announcing the service, Spotify explains; “Discover Weekly combines both your personal taste in music with what others are playlisting and listening to around the songs that you listen to” (Spotify Press, 2015). This methodology allows Spotify to circumvent inherent problems associated with collaborative filtering. One problem with collaborative filtering is that it does not take into account any knowledge about the music itself; it only cares about the usage patterns around it. As Brian Whitman of The Echo Nest puts it “A Beatles album on Amazon will simply show that listeners also bought other Beatles albums, while the closed loop of popularity bias makes it nigh impossible for new music to enter the system” (as cited in Vanderbilt, 2014). To solve this problem, Spotify’s Discover Weekly correlates knowledge about listeners with insight into music content.

However, Spotify and its music streaming competitors also recognize that knowing a listener’s overall taste in music is less important than knowing what that listener actually wants to hear at a particular moment in time. “[A] person’s preference will vary by the type of music, by their current activity, by the time of day, and so on,” says Spotify’s Ajay Kalia. “Our goal then is to come up with a nuanced understanding of each portion of your taste" (as cited in Heath, 2015). In short, Spotify understands its listeners as multiplicities, rather than fixed and singular individuals. "We believe that it’s important to recognize that a single music listener is usually many listeners” says Kalia (as cited in Heath, 2015). As a result, like other online platforms, Spotify is increasingly focusing on context in an attempt to serve better recommendations.

The Contextual Turn

Many studies have demonstrated that listeners gravitate to music that matches their current context (Kim & Belkin, 2002; Lee & Downie, 2004; Krause et al., 2015; Hagen, 2015). For example, while commuting, people tend to listen to music that provides them with a safe haven. Kaminskas and Ricci (2012) have identified several different types of contexts that appear to be particularly important to listeners, including "environment-related context (location, time, weather), user-related context (activity, demographic information, emotional state of the user) and multimedia context (text or pictures the user is currently reading or looking at)" (Pichl et al., 2017).

In order to recommend music that matches these contexts, streaming platforms need to collect and aggregate data points on everything from a listener's location, to the content they are consuming, to their current emotional state. This is made possible by the proliferation of mobile devices such as the smartphone, which permits the collection of data points like location, motion, time of day, and nearby contacts. Increasingly, wearable 'smart' devices will provide continuous contextual signals that recommendation systems can draw on.[3]

Significant research is being devoted to developing context-sensitive algorithms (Pichl and Zangerle, 2015). What has been called "the contextual turn" (Pagano et al., 2016, p. 1) in recommender systems can be described as a move away from the 'Immutable Preference paradigm' (ImP). ImP assumed that the user was a fixed individual, whose "goals, needs, and tastes do not develop" and in turn, "that the set of items to be recommended remains relatively static" (ibid.). As Pagano et al. (2016, p. 1) write, a focus on context "overthrows the assumption

[3] Spotify has indicated that they are interested in developing ways to monitor heart rates and sleeping patterns of listeners so as to more accurately recommend music that corresponds to bodily states (Smith, 2014).

that personalization in recommender systems involves recommendation for specific individuals." Instead, a context-based recommender system, "personalizes to users' context states" (ibid) rather than to individual users.

At its extreme, context-based recommendation systems take the position that one equals one's context: "people have more in common with other people in the same situation, or with the same goals, than they do with past versions of themselves." (Pagano et al. 2016, p. 1). From this perspective, a music listener who is about to go for an early morning jog, has more in common with another jogger than with their own music preference 15 minutes earlier, when they were just waking up.

For Spotify, knowing more about the listener's environment helps the service better recommend music for the 'moment'. "We're not in the music space—we're in the moment space," Spotify's CEO told the *The New Yorker* in an interview (Seabrook, 2014). If Spotify, for example, knows that you typically run on weekdays at 7 a.m., it will start recommending running playlists like "Running Power" at that time. What is more, in 2015 Spotify announced that it was introducing an adaptive running feature. The feature uses the accelerometer built into your phone to track motion. Your running tempo is converted into beats per minute, which, in combination with your previous listening history, determines the songs that will be selected for your personal jogging playlist.[4]

In a presentation at the 2015 SXSW festival, Paul Lamere (2015) of The Echo Nest/Spotify argued that context is the new genre. He demonstrated that while 17 of the top 100 Spotify playlist names are genre-related, 41 of the top 100 playlist names are context-related. A

[4] Spotify has also introduced "Running Originals": modular tracks that dynamically adapt to your running tempo(see https://www.spotify.com/us/running/)

glance at Spotify's top playlists today reveals an abundance of context-descriptors like 'Party', 'Roadtrip' and 'Workout' – to name but a few. 'Context states' need not only describe activities, though. They can also capture listeners' moods. According to the music data analytics startup 'Entertainment Intelligence', listeners are increasingly consuming music by mood instead of genre (G. Delaney, personal communication, May 22, 2017). Spotify even organizes one of its playlist categories under the title "Genres & Moods", wherein listeners can choose between traditional genre categories like 'Jazz' and 'Soul' or mood-based playlists like 'Chill' and 'Relax & Unwind'. Paul Firth, head of Digital Music UK for Spotify's competitor Amazon Music, argues that mood categorization represents a much more natural way of thinking about music; one that is more representative of how people speak about music (Chacksfield, 2016). Firth is basing this assessment on how Amazon Music listeners request music through Alexa – the voice assistant for Amazon Echo's smart speaker. As Firth explains:

> The way people want to find music through Alexa is how you would speak to someone else about music. And that's very different from how you search for music through a search button on a streaming service - people speak very naturally about music (as cited in Chacksfield, 2016).

Verbal requests for 'happy music' or 'something a bit sad' initially presented the streaming service with a problem. How could Amazon's recommendation system distinguish between a specific request for Pharrell Williams' 2014 hit "Happy", and a more general desire for upbeat, cheerful tunes? In order to facilitate Amazon's music library for mood-based recommendations, Amazon had to tag every song in their catalogue with a specific mood. The first 5,000 were done manually, after which machine learning was utilized for the remaining 40 million tracks (ibid.). Adding all this metadata presents streaming platforms with one of the most significant challenges in preparation for the hands-free listening experience.

When Paul Lamere was director of developer platforms at The Echo Nest he enthusiastically pursued what he called the Zero UI Project. “The ideal music player has zero buttons,” he said in an interview. “When you get in your car, it automatically starts playing NPR. When you come home, it knows if your wife is home: if she is, it plays jazz on the stereo, and if not, it puts on death metal" (as cited in Brownlee, 2014). The goal, as he describes it, is to create a music player that knows precisely what music to play for any listener given their current context. The challenge, however, is to glean enough information from the listener, without them even needing to actively tell the service what they want to hear. Implicit signals such as “[e]very time a listener adjusts the volume on the player, every time they skip a song, every time they search for an artist, or whenever they abandon a listening session” (Lamere, 2014), must therefore be enough to reveal the listener’s music taste.

The Echo Nest cofounder Brian Whitman suggests that the future of listener understanding and segmentation will get deeper into how, when and where people actually interact with music. As he noted at a talk at Microsoft, "not just what they skip, ban and recommend, but when? Did they just break up with their girlfriend?" (as cited in Vanderbilt, 2014). An article in *Fast Company* went even further, musing that “the possibilities are limitless”:

> …Spotify could communicate with wearable devices such as the *iWatch*…to take your pulse and adjust the BPMs of your playlist to match when it detects you're at the gym… the zero UI music player of the future might stalk you on Facebook or Twitter to see what your mood is, and adjust the music it plays you accordingly (Brownlee, 2014).

Knowing Me, Knowing You

With online music streaming all listening time has become available for data mining and analysis. Detailed listening practices can now be collected and correlated with other sources of personal data. Every signal feeds into algorithms that work toward building a profile. Artists and tracks are matched with particular listener profiles. Music, as well as listeners, are being classified and categorized.

However, this is not the type of categorization that characterized broadcast media audience research. What Cheney-Lippold (2011, 176) terms “cybernetic categorization” captures how a category’s meaning can now be realigned according to contextual cues. This indicates a move from blunt genre-based categories like “metalhead” to finely grained listener profiles like ‘suburbanite-with-teenagers-who-likes-Beyonce-but-also-likes-obscure-80s-metal-when-alone-in-the-car’.

However, an important question must be asked: when determining context, which data points will count and which data points will be discounted? In the example above of the Beyonce/Metal-loving suburbanite, should the weather or the season influence the music recommended? What about the listener’s mood; the car she is driving; where she is going; what she had for breakfast…? Everyday life can be sliced and diced into an innumerable number of different contexts. What data points will be used to build listening context?

Furthermore, which contexts will playlists be built around? Context may be king but which contexts will rule on music streaming platforms? In October, 2016, Spotify introduced ‘Branded Moments’. Through this feature, Spotify promised its advertisers to leverage “our unique data and insights” in order to “identify — in real-time — what a listener is doing, and give brands an opportunity to *own that moment*” (emphasis added). Initially, it appears that these branded moments will be organized around six contexts: ‘chill time’, ‘workout’, ‘party’, ‘dinner’, ‘focus’ and ‘sleep’. Bacardi, Gatorade and Bose are among the big brands making up the “select launch partners” for ‘Branded Moments’: Bacardi on 'Party', Gatorade on 'Workout', and Bose on 'Chill'. Interestingly, Spotify states that these contexts have been chosen “so brands have the opportunity to reach listeners in *all* aspects of their day” (Spotify For Brands, 2016) (emphasis added).

It is not surprising that these are popular contexts in which to listen to music. However, as Seaver (2015: 1106) points out “[a]s corporations turn their data mining attention to context, they have the power to impose and normalize certain modes of contextualization at the expense of others”. They will also seek to define these contexts. In turn, we could thus ask; how is context not just representing, but actually constructing the individual music listener?

Of course music listeners are never passive products of the categories and profiles generated about them. From the earliest days of music recommender systems, listeners have tried to trick or ‘hack’ their favorite services in an attempt to generate better recommendations. For instance, earlier research on how listeners used recommendation engines demonstrated that MusicFX users “changed their music preferences to make sure that music they liked a lot was more likely to play than music they could merely tolerate” (Konstan & Riedl, 2012, 114). More recently, Anja Nylund Hagen’s (2015) qualitative research on streaming platform users reveals how playlist curation provides listeners with a sense of control over their listening practices. Listeners are increasingly aware that the recommendations that surface on streaming platforms are a result of their every action being monitored and assessed. It is still an open question, though, as to whether - or to what degree – such knowledge might affect listening behaviour itself.[5]

[5] For example, see the Spotify Community discussion at https://community.spotify.com/t5/Desktop-Linux-Windows-Web-Player/Discover-Weekly-Is-there-anyway-of-telling-Spotify-not-to-track/td-p/1347197

At the moment, the data insights streaming platforms glean from their listeners are utilized to more accurately recommend music to listeners. However, real-time data feedback allows for highly detailed A/B testing of songs. It also extends and amplifies the modular potential of popular music, allowing songs to be rearranged, repackaged, and reformatted to fit the perceived tastes of particular listener profiles. The question that seems to naturally flow from this is: how long until music is tailor-made to match listener profiles? What is more, following Netflix's lead, will music streaming services leverage their data insights to circumvent record labels and produce their own original music content?[6]

As scholars have recognized the challenge of big data is not in collecting it, but in "figuring out how to make sense of it" (McCosker & Wilken, 2014). There is so much data, that the problem that now confronts everyone in the industry – from the independent artist, to the streaming platform, to the major label executive – is how to understand and effectively operationalize all this data. How streaming platforms deal with this data deluge - how they decide what data to value and what to discard - will shape the future of music consumption and discovery.

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[6] There has been some speculation amongst music industry experts and insiders that Spotify is moving towards negotiating record label-style deals with artists (Constine, 2017) in order to become a "next generation 'label'" (Mulligan, 2016). What is more, in August 2016, music industry journalist and commentator Tim Ingham revealed that Spotify was already producing its own content in order to fill out playlists and reduce its royalty payments to record labels (see Ingham, 2016).

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